

Estimating the Effect of the Chesapeake Bay Program on Application Rates
For Enrollment in the Environmental Quality Incentive Program:
A Case Study of Pennsylvania

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**Estimating the Impact of the Chesapeake Bay Program on Application Rates for Enrollment in the Environmental Quality Incentive Program:
A Case Study of Pennsylvania**

This paper is an investigation of the application of propensity score matching (PSM) to evaluate the impact of the Chesapeake Bay Program (CBP) on farmers' willingness to participate in the United States Department of Agriculture Environmental Quality Incentive Program (EQIP). The Chesapeake Bay Program is the nation's premiere large-scale watershed protection partnership program. The underlying premise of this study is that the CBP has an effect of farmers' voluntary adoption of farm conservation practices. This effect occurs via the CBP's educational out-reach and program initiatives directed to members of the farm community.

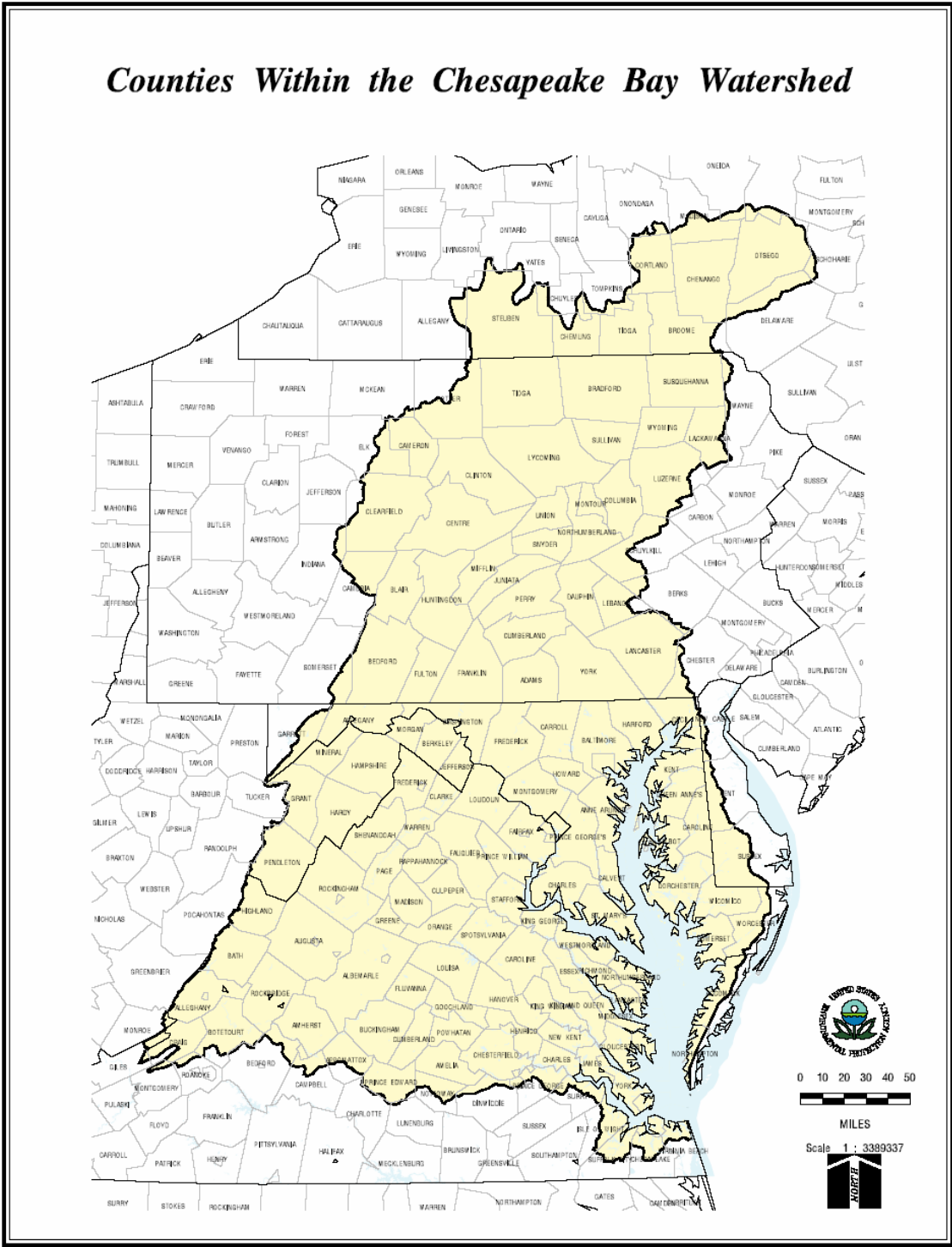
The CBP is a multi-faceted, comprehensive, and complex environmental program. This study is an initial attempt to estimate its impact. The study is limited in scope. The analysis is conducted over one state, Pennsylvania, and uses one conservation program, Environmental Quality Incentive Program (EQIP). Thus, the study is not presented as an extensive nor comprehensive evaluation of the CBP's impact. Rather, the study demonstrates a potential quasi-experimental method for conducting impact analysis with application to watershed protection programs.

The outcome variable for this study is county EQIP application rates. Although the null hypothesis of no impact cannot be rejected, the study illuminates potential areas for further investigation.

The Chesapeake Bay Program is the nation's premiere large-scale watershed protection partnership program. The program was established in 1983 to restore the water quality and ecological health of the Chesapeake Bay and the surrounding 64,000 square mile Chesapeake Bay watershed. The three signatory states to the Chesapeake Bay Agreement are Virginia, Maryland, and Pennsylvania. In addition, representatives for the District of Columbia, the United States Environmental Protection Agency (EPA), and the Chesapeake Bay Commission serve on the Chesapeake Bay Program Executive Council.

The watershed boundary and program service area of the Chesapeake Bay Program is depicted in Figure 1. Although funding for the program comes from EPA, the CBP is unique among EPA programs because the agency has relinquished governance of the program to the Chesapeake Executive Council. The Council has no regulatory authority. The CBP uses a management structure primarily based on consensus and voluntary action. The regulatory measures enacted to restore the environmental health of the bay are accomplished through the individual state

Figure 1. Chesapeake Bay Watershed Boundary and CBP Program Area



legislative assemblies. The role of the states is demonstrated by the enactment of 58 environmental statutes pertaining to the Chesapeake Bay since the 1983 Agreement, of which 9 are federal laws, and 49 are state laws.

The CBP has evolved into a comprehensive basin-wide bay restoration program. The CBP has successfully expanded its realm of partnerships and sphere of influence to include a multitude of local and state agencies, four interstate commissions, and thirteen federal agencies with an office or program dedicated to the Chesapeake Bay. The CBP has more than 50 subcommittee and work groups. The CBP has cultivated partnerships with 11 university environmental research centers and has affiliation with more than 700 citizen and watershed stakeholder groups.

The CBP is a voluntary partnership among federal, state, and local governmental units, university research centers, and environmental, industrial, and agricultural interest groups. Although the CBP has no direct regulatory or enforcement powers, it establishes water quality restoration goals, identifies research priorities, coordinates watershed protection grants, and provides funding for environmental education programs. The Chesapeake Bay Program serves as the catalysts for a diverse array of environmental initiatives to restore the ecosystem of the Chesapeake Bay watershed. Farmers do not join or enroll in the Chesapeake Bay Program. As a partnership of public and private organizations, the CBP does not have individual members. The underlying premise of this investigation is that the cumulative educational, research, and coordination activities of the CBP has a generalized “spill-over” effect on farmers’ willingness to participate in farm conservation programs.

Farmers are exposed to the activities of the CBP via research and educational outreach activities of the land-grant university agricultural extension service which partners with the CBP. Agricultural interest groups and farm associations participate

with the CBP in implementing demonstration projects designed to reduce agricultural non-point source pollution. Individual farmers may choose to become members of local watershed organizations or regional environmental organizations such as the Chesapeake Bay Foundation which is an active partner in the CBP. Farmers are also exposed to the CBP activities via outlets for local and regional news.

Background

The Chesapeake Bay estuary is located along the mid-Atlantic seaboard of the United States. The Bay's water quality, ecology, and fisheries have exhibited significant degradation during the past 40 years. The Bay's current ecological productivity level is estimated as one-quarter of its historic level (Pierno 2004). Nutrient pollution is the greatest of all recognized threats to the ecological health of the bay (Cronin 1967; Boesch 2004).

In response to the declining ecological health and corresponding economic loss emanating from the collapse of shellfish and fisheries industries, the Chesapeake Bay Program (CBP) was inaugurated in 1983 with the signing of the Chesapeake Bay Agreement by the states of Maryland, Pennsylvania, and Virginia, the District of Columbia, the Chesapeake Bay Commission, and the United States Environmental Protection Agency. The Agreement institutionalized a regional collaborative and voluntary approach to restoring and protecting the waters of the Chesapeake Bay and surrounding watershed. In 1999 the waters of the Chesapeake Bay were formally listed as impaired by the U.S. Environmental Protection Agency in compliance with Section 303 (d) of the Clean Water Act.

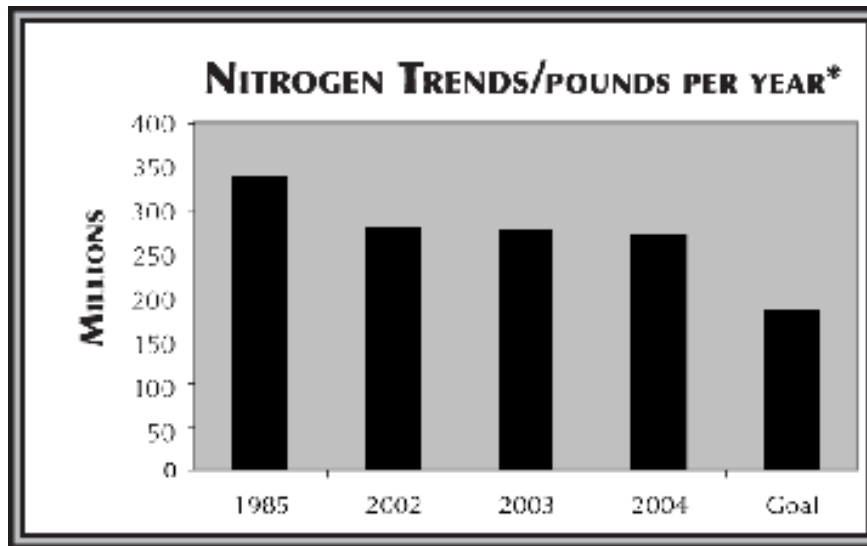
The Chesapeake Bay Program is one of 28 large-scale eco-system restoration programs in the United States. The Chesapeake Bay watershed is 64,000 square miles and is the largest estuary drainage basin in the world. 16 million people reside in the

basin. 80% of the total basin area is located in the three states of Maryland, Pennsylvania, and Virginia. The remainder is located in the headwater states of New York, Delaware, and West Virginia. Agriculture accounts for 30% of total land use in the basin, and is the source for nearly 50% of total nutrient loadings to the Bay. The CBP established the goal of reducing total nutrient loadings to the Bay by 40% below the annual loadings of 1985 which was established as the base level for comparisons of future reductions. Achieving a 40% reduction below the 1985 nutrient loadings is necessary to restore the Bay's ecological health.

Problem Statement

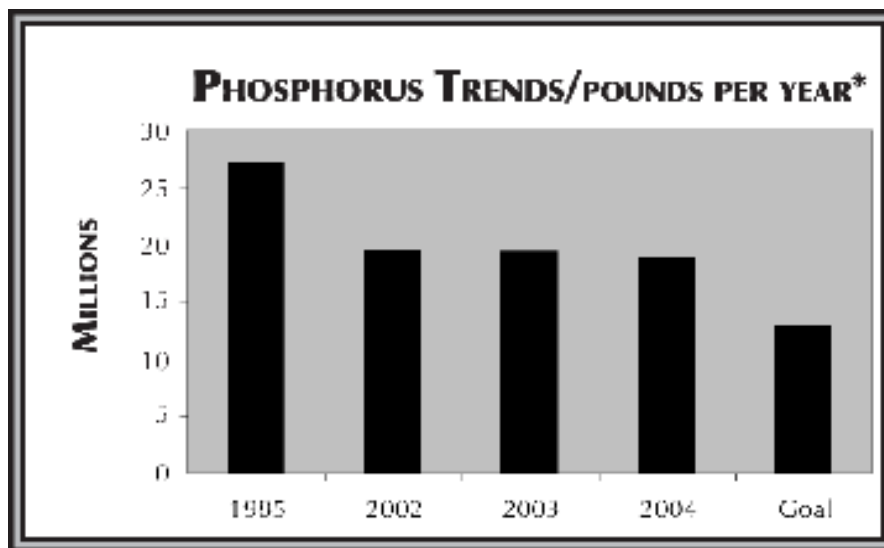
The Chesapeake Bay Program is operating under a court agreement to achieve its goal of nutrient reductions by 2010. If the goals are not achieved, the Environmental Protection Agency will be required to enforce new regulations to reduce nutrient loadings from non-point pollution sources. This will include new regulations of agricultural production to reduce nutrient enrichment. Although the CBP was successful reducing nutrient loadings to the bay during the period 1990 – 2000, Figures 2 and 3 illustrate that during recent years CBP efforts have failed to result in sustained nutrient reductions.

Figure 1. Nitrogen Loadings 1985 – 2004 and CBP Goal



Source: Bay Journal 2006

Figure 2. Phosphorus Loadings 1985 – 2004 and CBP Goal



Source: Bay Journal 2006

A challenge confronting the Chesapeake Bay Program is the necessity to reduce agricultural nutrient enrichment and maintain caps on future loadings once target reduction levels are obtained. One assumption for this paper is reduction of residual agricultural nutrients is positively correlated with implementation of agricultural conservation practices. The strength of the positive correlation varies significantly

due to variation in an array of random variables such as level of effort, frequency of program participation, and type of conservation practice. Evaluating environmental outcomes attributed to adoption of conservation practices is extremely challenging due to the complexities of aggregating individual loadings from multiple non-point sources, changing land use patterns, changes in management practices, and perhaps most significant of all is the variability of climate conditions. No attempt is made in this paper to evaluate the environmental outcomes attributed to the Chesapeake Bay Program.

Reducing residual nitrogen and phosphorus loadings from commercial and organic fertilizers will require the active participation and on-going commitment of the agricultural sector. Soliciting the voluntary participation and support of the agricultural sector requires sustained educational out-reach efforts funded by the CBP and its partners.

There is increasing interest in the potential gains in nutrient reductions from implementing nutrient trading programs between point-source and non-point source contributors. Knowing if the CBP currently affects participation rates in farm conservation programs is useful information for consideration of designing future CBP programs. Knowing if the CBP has a positive effect on willingness to participate in a conservation programs is one criterion to evaluate the CBP's performance.

This analysis is limited to a farmer's willingness to enroll in the Environmental Quality Incentive Program (EQIP). The Environmental Quality Incentive Program is one of 20 farm conservation programs administered nation-wide by the United States Department of Agriculture Natural Resources Conservation Service (NRCS). EQIP is a voluntary program. The purpose of the program is to promote agricultural

production and concurrently reduce environmental problems attributed to agriculture. This goal is partially accomplished by providing cost-share payments and technical assistance to participating farmers for the planning and implementation of structural, vegetative, and land management practices on eligible land to promote soil and water conservation practices. Under the 2002 Farm Bill, EQIP was authorized at an unprecedented funding level of \$6.1 billion over 5 years. EQIP is the major source of cost-share funds for addressing environmental problems attributed to agricultural production and has widespread support among the farm community (Zinn 2005).

The Pennsylvania Department of Environmental Protection (DEP) and the United States Geological Survey (USGS) estimated reductions in nitrogen and phosphorus loadings to the Chesapeake Bay Watershed which could be attributed to different state and federal programs. For the 4 state and 3 federal programs, conservation practices funded under EQIP accounted for 50% of total nitrogen reductions from agriculture and 60% of total phosphorus reduction from agriculture during calendar year 2000 (Pennsylvania Department of Environmental Protection 2002). The total agricultural related reduction was estimated at 10,663,300lbs of nitrogen and 319,229lbs of phosphorus. Estimates from the Chesapeake Bay Watershed Model were criticized in a General Accounting Office Report for over-stating the level of nutrient reduction attributed to best-management practices (GAO 2005). Although the above estimates likely over-state the extent of nutrient reductions, EQIP likely accounts for the highest percentage of nutrient reductions of all state or federal agricultural conservation programs.

Because a farm operator is eligible to enroll in a multiple of conservation programs such as the Conservation Reserve Program (CRP), the Conservation Reserve Enhancement Program (CREP), Wetlands Reserve Program, and the Wildlife

Habitat Incentive Program (WHIP), this initial study is limited to one program to avoid double-counting multiple applications from the same farm operator as a measure of willingness to participate in conservation program.

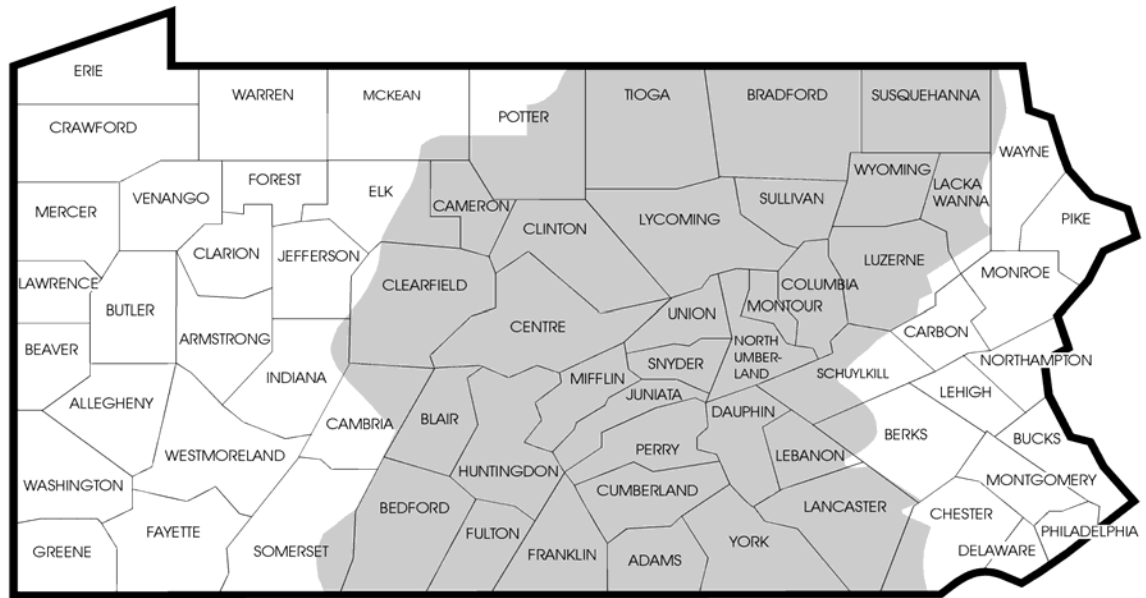
Study Area

The state of Pennsylvania is the pilot-study area. Of the 67 counties located in Pennsylvania, 36 counties participate in the Pennsylvania Department of Environmental Program (DEP) Chesapeake Bay Program. Figure 2 shows the location of the Chesapeake Bay basin and service area of the Chesapeake Bay Program in Pennsylvania. Approximately 30% of the surface area of the Chesapeake Bay watershed is located in Pennsylvania.

Table 1 lists the counties and corresponding land area in the Chesapeake Bay watershed. For the balance of this paper, the Chesapeake Bay watershed will be referred to as the basin. Of the 67 counties located in Pennsylvania, 43 counties have a portion of their land area in the basin. 33 of the 67 counties have 50% or more of their land area in the basin, and 31 of the 67 counties have 75% or more of land area in the basin.

The area of the Chesapeake Bay watershed located in Pennsylvania is referred to as the Susquehanna River Basin. The Susquehanna River is the largest of the nine major Bay tributaries and flows 450 miles through New York and Pennsylvania.

Figure 2. Study Area: State of Pennsylvania and In-basin Counties.



Source: Pennsylvania Department of Environmental Protection Chesapeake Bay Program. Shaded area illustrates the Chesapeake Bay watershed.

Table 1: Percentage of County Land Area in the Chesapeake Bay Watershed 2006

	County	Actual %	If County has portion of land area in basin T=1	If county has 50% or more of its land area in basin T=1	If county has 75% or more of its land area in basin T=1
1	Adams	100	1	1	1
2	Bedford	100	1	1	1
3	Berks	7.1	1	0	0
4	Blair	100	1	1	1
5	Bradford	100	1	1	1
6	Cambria	42.3	1	0	0
7	Cameron	100	1	1	1
8	Carbon	1	1	0	0
9	Centre	100	1	1	1
10	Chester	18.5	1	0	0
11	Clearfield	90.7	1	1	1
12	Clinton	100	1	1	1
13	Columbia	100	1	1	1
14	Cumberland	100	1	1	1
15	Dauphin	100	1	1	1
16	Elk	32.4	1	0	0
17	Franklin	100	1	1	1
18	Fulton	100	1	1	1
19	Huntingdon	100	1	1	1
20	Indiana	7.5	1	0	0
21	Jefferson	1	1	0	0
22	Juniata	100	1	1	1
23	Lackawanna	84.7	1	1	1
24	Lancaster	99.6	1	1	1
25	Lebanon	85.3	1	1	1
26	Luzerne	85.3	1	1	1
27	Lycoming	100	1	1	1
28	McKean	2.2	1	0	0
29	Mifflin	100	1	1	1
30	Montour	100	1	1	1
31	Northumberland	100	1	1	1
32	Perry	100	1	1	1
33	Potter	62.8	1	1	0
34	Schuylkill	51	1	1	0
35	Snyder	100	1	1	1
36	Somerset	13.6	1	0	0
37	Sullivan	100	1	1	1
38	Susquehanna	100	1	1	1
39	Tioga	100	1	1	1
40	Union	100	1	1	1
41	Wayne	7.9	1	0	0
42	Wyoming	100	1	1	1
43	York	100	1	1	1
Total			43	33	31

Source: Natural Resources Conservation Service

The river delivers 50% of the freshwater flow to the Bay and accounts for 60% of the total nitrogen load and 34% of the total phosphorus loads to the Bay. The Susquehanna River is the largest tributary source of nutrient and sediment loadings. Approximately 75% of the 27,500 square mile Susquehanna River basin area is located in Pennsylvania. Land use in the Susquehanna basin consists of forest at 60% and agriculture at 30%.

36 counties located in the Chesapeake Bay watershed choose to participate in the Pennsylvania Department of Environmental Protection (DEP) Chesapeake Bay Program in 2003-2004. Each county that participates in the program receives funding for a watershed technician. Four participating counties received funding to support 2 or more watershed technicians. To maintain a comparable level of “treatment effect” across participants only those counties with 1 technician will be included in the set of participants, and the 4 counties with 2 or more watershed technicians will be omitted from analysis. The four counties are Bradford, Dauphin, Lancaster, and York. All four counties are leading counties in Pennsylvania’s agricultural production. Bradford County, however, displayed an unusual outcome of submitting 85 unfunded applications in 2004. This outcome is three times greater than any other county and the observation is treated as an outlier.

Five non-participant counties were omitted from the dataset. One county displayed an outcome variable that was also an extreme outlier with an EQIP participation rate of 8.6 percent; the next highest rate was 4%. The 8 percent rate was attributed to a total of 3 applications and a total of 35 farms in the county. This observation significantly influenced the mean non-participant rate, and is not representative of non-participant counties. Four additional non-participant counties were omitted because the likelihood of the counties choosing to participate in EQIP

was deemed to be nearly zero. Two counties, Philadelphia and Pike have 9 and 50 farms respectively and have no acreage in the EQIP program or prior EQIP applications. Two counties, Forest and Elk have neither EQIP applications nor acreage enrolled in EQIP for prior years. Further more, both counties have 90% or more forest cover. They are predominately forested with no agriculture.

Because the dataset for this study consists of only a total of 58 observations, with 32 participants and 26 non-participants, the emphasis of the remainder of the paper is on the steps and application of matching as an estimation method. The purpose of this paper is to serve as a preliminary study to investigate constructing a model for matching on propensity scores that may have application to evaluating large-scale watershed restoration programs. If applied to the entire Chesapeake Bay basin there would be a total of 147 counties located in the basin and 40 out-basin counties. The focus of this paper is on identifying potential covariates for estimating the propensity scores and analyzing the common support of the scores and balancing properties. The current sample size is too small to construct statistically rigorous estimates of the average treatment effect of the treated (ATET).

An estimated 26,800 farms are located in “participant” counties, and 20,750 farms are located in nonparticipating counties. The 26 non-participant counties will be used to estimate the missing counterfactual for purpose of matching, which is defined as the expected EQIP application rate for participants if they did not have a watershed technician.

CBP funding is allocated to a county conservation district to support a watershed technician for the purpose of working with farm operators to design and implement farm conservation practices. Approximately 2 million dollars is allocated annually to participating conservation districts located within the basin. Separate CBP funds to

cost-share implementation of farm conservation practices have decreased during the past 10 years. However, the decrease in CBP cost-share funds for farm conservation projects has been off-set by a significant increase in USDA funding for farm conservation programs. For example, funding for EQIP in Pennsylvania has increased from 2.5 million dollars in FY2002 to 10.5 million dollars in FY2005.

The purpose of this paper is to estimate if the presence of a CBP funded watershed technician has a positive spillover effect on farmers' willingness to enroll in EQIP. While the EQIP program is administered by the Natural Resources and Conservation Service (NRCS), CBP watershed technicians commonly assist farmers with completing enrollment applications for conservation cost-share funding for multiple programs (Chesapeake Bay Cost-share Program, Environmental Quality Incentive Program (EQIP), Conservations Reserve, Wetland Reserve, and Conservation Reserve Enhancement Program (CREP)). Thus a potential measure of the CBP impact could be observed higher program application rates from farmers located in "participant" counties with a CBP watershed technician compared to program application rates from "non-participant" counties absent a CBP watershed technician.

In the context of evaluation literature, the three pillars of the counterfactual model are treatment, individuals, and potential outcomes (Caliendo 2005).

In this paper, treatment is defined as the program and educational out-reach initiatives of the Chesapeake Bay Program and CBP watershed technicians. The effort of the CBP watershed technicians is intended to increase the conservation behavior of farm operators located in the counties of the Chesapeake Bay watershed. Counties located in the basin which applied for a CBP watershed technician are

labeled as “participant” ($D_i=1$), and counties without a CBP technician are labeled as “non-participant” ($D_i=0$). All data for this study is at the county level.

The outcome variable is EQIP application rates by county for FY2004. EQIP application rate is calculated by dividing the total number of EQIP applications received by NRCS per county by the total number of farms per county. Total applications consists of the sum of funded applications plus unfunded. The research question is whether the presence of the Chesapeake Bay Program results in higher EQIP application rates for counties located in the CBP service area?

Willingness to participate is demonstrated by submission of an application for enrollment in EQIP. The estimation method is propensity score matching. Matching is one method which can be used to estimate treatment effects using observational studies when a randomized control group is not available for purposes of comparing outcomes with treatment and without treatment (Winship 2004; Dehejia 1998; Rosenbaum and Rubin 1983).

The use of matching as a method to reduce bias in the estimation of treatment effects with observational datasets have become increasingly popular in medical trials and in the evaluation of economic policy intervention (Becker 2006; Wooldridge 2002). In the environmental economics literature matching has recently been extended to evaluation of environmental programs (Greenstone 2002; List 2002; Frondel 2001).

Literature Review

The Chesapeake Bay is likely the most extensively researched estuary in the country. Beginning in the 1960s and 1970s, Chesapeake Bay was one of the first major waterways where the federal government commenced long-term comprehensive water quality monitoring and land use analysis to identify the leading threats to the bay's ecology. Studies by the U.S. Army Corps of Engineers (1965-1978) and the United States Environmental Protection Agency (1977 – 1982) culminated in the establishment of Chesapeake Bay Program in 1983.

The institutional history of the Chesapeake Bay Program is documented in publications by Wennersten (2001), Ernst (2003), and Horton (1991). Many of the CBP partners publish annual reports pertaining to the Bay. The Bay Journal is one of the leading monthly news publication reporting on the affairs of the Chesapeake Bay Program Executive Council, and the scientific research and educational out-reach programs of CBP partners.

Boesch (2001) and Straver and Brinsfield (2001) analyze the impact and role of agriculture in restoration of the Chesapeake Bay. There is a standing CBP scientific committee assigned to research agricultural related issues. During the past 20 years an extensive body of literature in the field of environmental and agricultural economics has developed pertaining to policy and program design of farm conservation programs (Ribaud, Horan, and Smith 1999; Russell and Shogren 1993).

Accompanying this literature has been research to estimate the determinants of participation in farm conservation programs, and comparisons of outcomes for voluntary and mandatory farm conservation programs. Information on the factors that influence a farm operator's willingness to adopt farm conservation practices can be used to design effective programs.

A national study by the Economic Research Service examined the business, operator, and household characteristics of farms that have adopted conservation-compatible practices with and without federal support (Lambert et.al, 2006). “Conservation-compatible practices that reduce the operator’s time or out-of-pocket labor and input costs for producing a commodity without requiring specialized knowledge have been widely adopted. Practices such as conservation tillage, crop rotation, and use of insect/herbicide-tolerant plants have been extensively adopted. Conservation-compatible practices that require a sizable investment of management time or heightened skill are less likely to be adopted by farm operators who focus primarily on nonfarm activities (Lambert 2006).”

Selected findings identified that the availability of expert advice may help induce adoption of conservation practices. As information-intensive technologies that aid crop input management become more complex, technical assistance from agricultural extension and certified crop and nutrient management consultants will increase in importance.

Farm payments may influence the conservation behavior of farmers by reducing the financial risk of changing farm practices. Farm payment recipients are more likely to have adopted conservation-compatible practices than farmers growing nonprogram crops and livestock.

Operators of small farms, particularly those who are retired or whose primary occupation is not farming, are less likely to adopt management-intensive conservation farming practices.

The number of conservation activities practiced was positively correlated with land ownership. Larger farm operators who were raised on a farm tend to practice a wider array of conservation practices. Farm proximity to a water body and location on

environmental sensitive land is positively correlated with the number of conservation activities practiced by a farm.

Off-farm income as a proportion of total farm household income was negatively associated with the likelihood that an operator participated in conservation programs. In a random sample survey of 100 farm operators located in two counties in Virginia, Norris and Batie estimated determinants of farmers' soil conservation decisions using an application of Tobit regression (Norris and Batie 1987). Factors found to be significant and positive included farmers' perception of erosion problem, farm size, income, and existence of conservation plan. Off-farm employment, debt level, and tenure were significant and negative. Farmers who graduated only from high school but not college invested less in conservation practices than farmers who graduated from college.

Findings from the above studies identify variables that influence farmers' decisions to adopt and/or participate in conservation programs. The findings will be used for selecting a set of covariates for purposes of matching counties. Table 2 lists variables and the expected sign of the correlation coefficient to participation in farm conservation programs as identified in selected references.

Challenges to conducting evaluation of environmental programs are well documented (Susskind 2001; Portney and Stavins 2000; Knapp and Kim 1998). Knapp (1998) uses the following categories for classifying methods of environmental program evaluation: process, impacts, and efficiency. Process evaluation addresses implementation, impact evaluation addresses outcomes, and efficiency evaluation addresses program benefits and costs.

A review of program evaluation is contained in Borland, Jeng, and Wilkins (2005). Impact evaluation is distinguished from process and efficiency evaluation. Whereas outcome monitoring would report the total number of EQIP applications received from operators located in CBP counties, impact evaluation is a measure of how an outcome variable for program participants is changed because of the participation. This measure is the difference between a participant's outcome compared to what the outcome would have been had they not participated in the CBP.

For purposes of analyzing if the presence of a large-scale ecosystem restoration program such as the CBP influences farmers' willingness to participate in conservation programs, the counterfactual model is used for estimating casual effects.

Table 2: Expected Association between Selected Variables and Farm Participation in Conservation Program

Variable	Percent of land enrolled In CRP/CREP/WRP	Number of conservation structures
Farm Characteristics		
High-value crops	No association	Negative
Grain crop	Negative	No association
Sole owner	Positive	Positive
Government payment	Positive	No association
Household characteristic		
Household size	No association	Positive
Operator raised on farm	No association	Positive
Female operator	Positive	No association
Environmental characteristics		
Highly erodible land	No association	Positive
Farm next to water source	No association	Positive

Source: Economic Research Service 2006

Variable	Adoption of conservation practices
Farmer characteristics	
Perception of problem	Positive
Education	Positive
Farm characteristics	
Off-farm employment	Negative
Debt	Negative
Size	Positive
Existence of Nutrient Plan	Positive

Source: Norris and Batie 1987

Variable	Adoption of conservation practice
Farmer	
Age	Positive/Negative
Education	Positive
Farm characteristic	
Size	Positive
Sole operator	Positive
Tenure	Positive/Negative
Gross Income	Positive
Off-farm income	Negative
Succession	Positive
Encroachment of adjacent development	Negative
Behavioral and Attitudes	
Information	Positive
Environmental education	No association
Communication with resource agencies	Positive
Governmental trust	Positive
Communication with other farmers	Positive
Prior participation	Positive

Source: Larson 2006 Literature Review

The application of matching has received limited application in the environmental economics literature. List (2003, 2004) used matching at the county level and difference in difference estimators to estimate the impact of new source review requirements of the Clean Air Act on decisions to start-up new manufacturing plants and on decisions to invest in new capital. Greenstone (2004) used county level matching to evaluate if enactment of the Clean Air Act caused decline in sulfur dioxide concentrations over the period 1980 – 1990.

The matching literature is broad and extensive. The fundamental microeconomic problem of evaluating policy intervention is characterized as one of “missing data”. At any moment, an individual unit is either in the program (participant) or not in the program (non-participant), but cannot be observed in both states. The missing observation is the counter-factual that is estimated using matching methods. The seminal work of Rubin and Rosenbaum renewed interest in the theoretical and empirical performance of matching estimators during the 1980s and 1990s, and continues today (Rubin 1974, 1977; Rosenbaum and Rubin 1983). Reviews of experimental and quasi-experimental methodologies using matching estimators are contained in Imbens 2004, Dehejia 1998, Hill 2004, Winship 2004, Blundell and Dias 2002, Heckman et. al. 1997, Smith 1997, Wooldridge 2002, and Rosenbaum 1995.

Counterfactual Model

This section uses the exposition and notation by Dahajia (1998), Wooldridge (2002), Frondel (2001), and Smith (2006) to describe the estimators and assumptions of matching methods. The notation for estimating a potential outcome was first introduced by Neyman (1923) and Fisher (1935) for the analysis of random events, and renewed by Rubin (1974, 1977, and 1978). The counter-factual model is presented in the context of estimating the effect of the Chesapeake Bay Program on county EQIP application rates.

There is an extensive literature devoted to the philosophical concepts and definitions of what constitutes a cause and effect relationship, and the necessary conditions under which a relationship can be deemed casual (Winship and Sobel 2004). During the 1980s an explicit model of causal inference based on the counterfactual account of a casual relation was developed by statisticians and econometricians (Rosenbaum and Rubin 1983; Heckman 1989; Manski 1995; Heckman, Ichimura, and Todd 1997). The work has resulted in an extension of causal inference based on controlled experimental design methods. In the social sciences randomized assignment to a treatment group and control group often is not feasible or practical. The counter-factual model is premised on the metaphor of an experiment where the goal is to estimate the effect of a particular ‘treatment’ (Winship and Sobel 2004) and treatment if often interpreted broadly (Wooldridge 2002).

For purposes of this paper treatment is defined as the educational out-reach and conservation programs administered by CBP partners for the purpose of increasing farmer’ adoption of conservation practices. The unit of observation is a county. The outcome variable is the EQIP application rate.

Notation

Let i index the counties in the study area, with $i = 1, 2, 3 \dots 67$

$D_i = (0,1)$ indicator of the treatment actually received by unit i

$D_i = 0$ if no participation in CBP

$D_i = 1$ if participant in CBP

Y_i = EQIP application rate for unit i

$= [(\text{Total number of EQIP applications by county } i) / (\text{number of farms in county } i)] * 100$

Symbolically, the evaluation problem can be represented as:

Y_{i0} = outcome of county i if non-participant.

Y_{i1} = outcome of unit i if participant.

The causal effect for unit $i = \Delta_i = Y_{i1} - Y_{i0}$

$Y_i = DY_{i1} + (1 - D)Y_{i0} \rightarrow$ the actually observed outcome of unit i

Let $X \rightarrow$ observable county characteristics that simultaneously influence the participation decision and the outcome variable and are unaffected by the outcome variable.

When participation is voluntary, one treatment effect that is of interest to policy makers is the expected treatment effect over the treated population (ATET), which is the mean effect of those units actually treated by the CBP.

$$\begin{aligned} \text{ATET} &\equiv \Delta |_{D=1} = E(\Delta_i | D=1) \\ &= E(Y_{i1} - Y_{i0} | D=1) \\ &= E(Y_{i1} | D=1) - E(Y_{i0} | D=1) \end{aligned}$$

The missing data problem of the counterfactual model is that only $E(Y_{i1} | D=1)$ is observed, while the term $E(Y_{i0} | D=1)$ is the counterfactual which can not be observed and thus must be estimated. Either Y_{i1} or Y_{i0} is observed for each county not both; cannot observe the nonparticipant outcome for participants, and can not

observe participant outcome for nonparticipant. For this paper, a county is treated by the CBP if it is a participant in the Pennsylvania Department of Environmental Protection (DEP) Chesapeake Bay Program during 2004.

While $E(Y_{i1} | D=1)$ is observed, $E(Y_{i0} | D = 1)$ is not. $E(Y_{i0} | D=0)$ is observed. If $E(Y_{i0} | D=0)$ is substituted for $E(Y_{i0} | D = 1)$, bias is equal to the difference between the two estimates $E(Y_{i0} | D = 1) - E(Y_{i0} | D=0)$.

As a thought experiment, if counties were randomly assigned to treatment

$$Y_{i1}, Y_{i0} \parallel D_i$$

$$\text{Implies } E(Y_{i0} | D_i = 0) = E(Y_{i0} | D_i = 1)$$

$$\text{Thus } E(Y_{i0} | D = 1) - E(Y_{i0} | D=0) = 0$$

In randomized experiments, use of the observed outcome for non-participants as an estimate of the missing counter-factual does not introduce bias in the estimator. “In an experimental approach, individuals in a population are randomly assigned between participation and non-participation to a program, and the outcome of interest is compared between those groups. Random assignment should generate two groups, participants and nonparticipant, where each group has the same average characteristics for both observable and non-observable attributes. Randomization tends to make treated and control groups comparable in terms of all observed and unobserved covariates (Rosenbaum 1995).”

Random assignment solves the evaluation problem by direct construction of the unobserved counterfactual. Matching solves the evaluation problem (the missing data problem of the counterfactual) by assuming that choice of participation is unrelated to the non-participant outcome conditional on some set of observable variables X (Smith 2006). This primary assumption is referred to as conditional independence

assumption (CIA), or independent treatment assumptions, or ignorability of treatment assumption, all conditional on a set of observable variables X .

“Matching uses data on non-participants to estimate the participant’s outcome as if they had not participated in the program. The term ‘matching’ is used since the comparison is made conditional on a set of observable variables, X , that affect both the outcome and likelihood of participation, yet are unaffected by participation (Borland 2005).”

The average treatment effect on the treated using a matching estimator is:

$$E(\Delta \mid D=1, X) = E(Y_1 \mid D=1, X) - E(Y_0 \mid D=0, X)$$

To be unbiased requires that $E(Y_0 \mid D=1, X) = E(Y_0 \mid D=0, X)$ with the interpretation that conditional on observable covariates, the outcomes for the non-participants after the start of the program must be the same outcomes that would have occurred for participants, had they not participated. This also requires that the decision whether to participate is not influenced by unobservable factors.

When the treated and control groups do not systematically differ from each other, conditioning on D_i in the expectation is not necessary. In the matching literature this is referred to as “Ignorability of treatment”. An additional requirement is that the outcome of unit i is independent of unit j , this assumption is referred to as the stable unit treatment value assumption (SUTVA).

The work of Rosenbaum and Rubin extended this estimation to non-experimental settings when randomization of treatment is not possible. The vector of covariates \mathbf{x} can be used to match units. The units would be stratified into bins, each defined by an observed value for \mathbf{x} ; placing two units into the same bin would be conditioning on \mathbf{x} . However, this method quickly becomes insurmountable. In a set of covariates where each variable is dichotomous the number of possible values for the vector \mathbf{x} will be 2^n . The likelihood of exact matches for each treated unit decreases as n increases.

Rosenbaum and Rubin demonstrated that matching on a set of covariates could be reduced to matching on a propensity score. Proofs are contained in Rosenbaum and Rubin (1983). The use of a propensity score reduces the dimensionality of the matching problem, and allows for matching on a scalar (Dehejia 1998).

Empirical Evaluation

Let N_1 be the number of counties that choose to participate with indices i contained in I_1 and the set of non-participant counties consists of N_0 with indices j contained in I_0 .

To estimate the program impact one would like to calculate:

$$ATE := \frac{1}{N_1, X} \sum_{i \in I_1, X} Y_{1i} - \frac{1}{N_1, X} \sum_{i \in I_1, X} Y_{0i}$$

As stated previously when discussing the population parameter, Y_0 is not observable for participants, and $\frac{1}{N_1, X} \sum_{i \in I_1, X} Y_0$ is unknown. This undetectable mean has to be replaced by an observable average (Frondel 2001).

Categories of estimators include before-after comparisons, cross-section estimators, and difference-in-difference estimators. This paper employs the cross-section estimator where the mean of the observed outcome of non-participants is used to replace the mean of the unobservable Y_0 for participants. The impact estimator of the average treatment effect on the treated is:

$$ATE := \frac{1}{N_1, X} \sum_{i \in I_1, X} Y_{1i} - \frac{1}{N_0, X} \sum_{j \in I_0, X} Y_{0j}$$

The condition underlying this estimator is: $E(Y_0 | D=1, X) = E(Y_0 | D=0, X)$. After matching on the propensity score, and satisfying the balancing requirements of the covariates, the above estimator is the difference of the simple average of the outcome variable (i.e. EQIP participation rate) for the matched participant counties minus the simple or weighted average of the matched non-participants.

Data Source and Variable Selection

All data is county level. There are 43 counties with a portion of their land surface located in the Chesapeake Bay watershed. 36 counties choose to participate in the Pennsylvania Department of Environmental Protection (DEP) Chesapeake Bay Program. Counties choosing to participate in the CBP received funding to support a watershed technician to work directly with farm operators. Technicians promote conservation practices and inform farm operators regarding opportunities to obtain cost-share funds to implement best management practices. The work of a watershed

technician augments the educational out-reach efforts of conservation districts. It is expected that the work of a CBP watershed technician is positively correlated with farmers' willingness to enroll in farm conservation programs. This effect is consistent with the variable of communication and trust identified as a potential determinant of farmers' willingness to adopt conservation practices listed in the literature review.

The outcome variable for the study is EQIP Application Rate. The variable is calculated by dividing total EQIP applications from each county by the total number of farms per county. This count does not include farmers willing to participate who did not submit an application. EQIP is funded over the five-year duration of the 2002 Farm Bill 2002-2007. Although applications are accepted on a rolling basis, NRCS encourages EQIP applicants to submit one application that will address multiple environmental concerns to avoid the practice of submitting applications each year. Data was not available to identify what percentage of applicants received prior EQIP funding. The Natural Resources and Conservation Service (NRCS) provided the count of total EQIP applications. County level data was compiled from the following sources:

Electronic databases:

- U.S. Agricultural 2002 Census
- County Business Patterns U.S. Bureau of Census
- USDA Economic Research Service
- Federal, State, and Local Governments Consolidated Federal Funds Report

Agencies:

- Pennsylvania State Conservation Commission
- Pennsylvania State Geospatial Technology Program and Land Analysis Center
- Pennsylvania Department of Agriculture
- Pennsylvania Department of Environmental Protection
- Pennsylvania Bureau of Forestry
- Natural Resources Conservation Service
- USDA Farm Service Agency
- Cumberland County Conservation District
- Lebanon County Conservation District

The set of covariates used to estimate the propensity score will be selected from the categories of farm characteristics, physical county attributes, and county level social and economic indicators. Appendix A contains the list of 79 variables assembled for consideration of being used as a covariate for estimating the propensity score

The conditional independence assumption (CIA) requires the outcome variable to be independent of treatment conditional on the propensity score. Only variables that simultaneously influence the decision to participate (binary $D_i=0$ or $D_i=1$) and the outcome variable (EQIP application rates) should be included in the logit model to estimate the propensity score. Furthermore only variables that are unaffected by the participation decision should be included. As a first step in selecting covariates, the correlation between 79 county attributes and participation and EQIP rates were calculated. From this list, 15 were identified as having higher correlation for both participation and EQIP rate relative to the other 64 variables. The selected variables are listed in Table 3. Inspection reveals that the correlation is weak for most variables with rates near 0.20.

Table 3. Selected Variables and Correlation with Treatment and Rate

	Variable	Correlation Coefficient	
		Treatment	Rate04
1	Farms with 500 to 999 acres	0.217	0.229
	p-value	0.102	0.083
2	Net Farm Income	0.551	0.208
	p-value	0	0.117
3	Percent county planted in crop	0.296	0.23
	p-value	0.024	0.083
4	Percent of county planted in corn crop	0.316	0.237
	p-value	0.016	0.074
5	Mean value equipment per farm	0.186	0.237
	p-value	0.162	0.073
6	Population 2000	-0.294	-0.175
	p-value	0.025	0.188
7	Number of Non-farm establishments with paid employees	-0.293	-0.171
	p-value	0.026	0.199
8	Percent of population with only high school degree	0.189	0.203
	p-value	0.155	0.127
9	Percent republican vote in 2004 presidential vote	0.471	0.259
	p-value	0	0.049
10	Number of hunting licenses	-0.25	-0.213
	p-value	0.058	0.108
11	ERS rural code	0.27	0.279
	p-value	0.041	0.034
12	Percent agricultural land within 150 feet of stream	0.267	0.221
	p-value	0.043	0.095
13	Number of acreage covered by nutrient management plans	0.48	0.184
	p-value	0	0.167
14	Number of EQIP contracts prior to 2004	0.212	0.29
	p-value	0.111	0.027
15	Number of housing units	-0.294	-0.174
	p-value	0.025	0.191

Economic theory, previous research, and information about the institutional settings should guide the researcher in building up the model (Caliendo 2005). An extensive review of the propensity score matching literature did not reveal prior empirical application to evaluating watershed protection programs. The selected variables for this study that have relatively higher correlation coefficient and correspond to conservation determinants identified in the agricultural econometrics literature include:

1. The number of farms with 500 to 999 acres.
Positive correlation.
Larger farms are likely to participate in working-land conservation programs such as EQIP than smaller “part-time” or “retiree farms”.
2. Net farm income.
Positive correlation.
Higher farm income shifts budget constraints to adopt conservation practices.
3. Percent of agricultural land within 150 feet of waterway.
Positive correlation.
Lambert (2006) reports farm next to stream as a statistical significant determinant for working-farms to participate in conservation programs.
4. Number of Non-farm establishments with paid employees
Negative correlation
Increased opportunity for off farm income associated with fewer enrollments in conservation programs.
5. Number of housing units
Negative correlation
The higher the number of housing units may be associated with increased opportunity for land development and subsequent reduced farm enrollment in conservation programs. However, increased housing stock may also increase societal pressure on farm operators to adopt conservation to reduce negative spillover effects.

Given the small sample size (58 observations) a parsimonious logit model was used to calculate propensity scores using four variables. One variable, percent of Republican vote in 2004 presidential election ranks near the top of correlation for both variables. Further investigation is warranted regarding the effect of this variable.

It was not included in the model given the uncertainty of its role in explaining the participation decision and outcome variable. However, this variable consistently is statistically significant in all model specifications using different covariates.

Descriptive statistics for the four covariates are listed in Table 4.

Table 4. Descriptive Statistics for Selected Covariates

Variable	Mean for Non-participants	Mean for Participants	P-value for two-sided t-test of difference in means $\Pr(T > t) =$	Definition and Source
Farm 500-999 acres	40.4 (30.9) n=26	54.8 (34.1) n=32	0.098	Number of farms with 500 to 999 acres <i>Agricultural 2002 Census</i>
Number of Firms	6119 (8365) n=26	2520 (2712) n=32	0.044	Number of non-farm establishments with paid employees <i>Current Business Patterns</i>
Percent agriculture within 150 feet of stream	7.44 (2.67) n=26	8.95 (2.83) n=32	0.042	Percentage of agricultural lands within 150 feet of waterway <i>Pennsylvania Conservation Commission</i>
Number of EQIP Applications prior to 2004	3.96 (3.08) n=26	5.75 (4.89) n=32	0.096	Total number of EQIP applications (funded and unfunded) prior to FY2004 <i>Natural Resources Conservation Service</i>
Standard Deviations in parentheses				

Estimation

Dehejia (1998) present the following algorithm for estimating the propensity score:

- Start with a parsimonious logit function to estimate the score
- Sort data according to estimated propensity score (ranking from lowest to highest).
- Stratify all observations such that estimated propensity scores within a stratum for treated and control units are close (no significant difference); e.g. start by dividing observations in blocks of equal score range (0-0.2...0.8-1).
- Statistical test: for all covariates, differences-in-means across treated and control units within each block are not significantly different from zero.

1. If covariates are balanced between treated and control observations for all blocks, stop.
2. If covariate i is not balanced for some blocks, divide block into finer blocks and re-evaluate.
3. If covariate i is not balanced for all blocks, modify the logit by adding interaction terms and/or higher-order terms of the covariate i and re-evaluate.

The propensity score matching values were estimated using Stata9.1 Software.

The program algorithm is similar to the above method which balances the propensity scores within k user specified equally spaced intervals; the default is 5 intervals.

Balancing implies that the average propensity score for the in-basin and out-basin counties does not differ within intervals.

The statistical test for balancing covariates requires that within each interval, the results from t-tests of mean differences for each of the covariates used in the logit regression reveals that the mean of the covariate does not differ between in-basin and out-basin counties.

The balancing condition was cited earlier as the Ignorability of treatment assumption, and symbolically is represented as $T \perp X | p(X)$. To satisfy the balancing property, observations with the same propensity score must have the same distribution of characteristics independent of treatment status. This condition requires that for each covariate, differences in mean across treated and control units within each interval are not significantly different from zero (Chen 2004).

Upon completion of estimating propensity score for each county, Stata Software can be used to estimate average treatment effects on the treated by matching on propensity scores. There are many methods in the evaluation literature for purposes of matching. This study presents results for two types of matching methods, nearest neighbor matching and radius matching. Matching on propensity scores is restricted to a

common support. Common support implies omitting all observations of participant county propensity scores that are above the maximum propensity score for the non-participant counties, and omitting all observations for non-participant county propensity scores that are below the minimum propensity score for the in-basin counties.

Results

A logit regression model was used to estimate county propensity scores. The dependent variable is binary, with participation designated as $D=1$, and non-participation $D=0$.

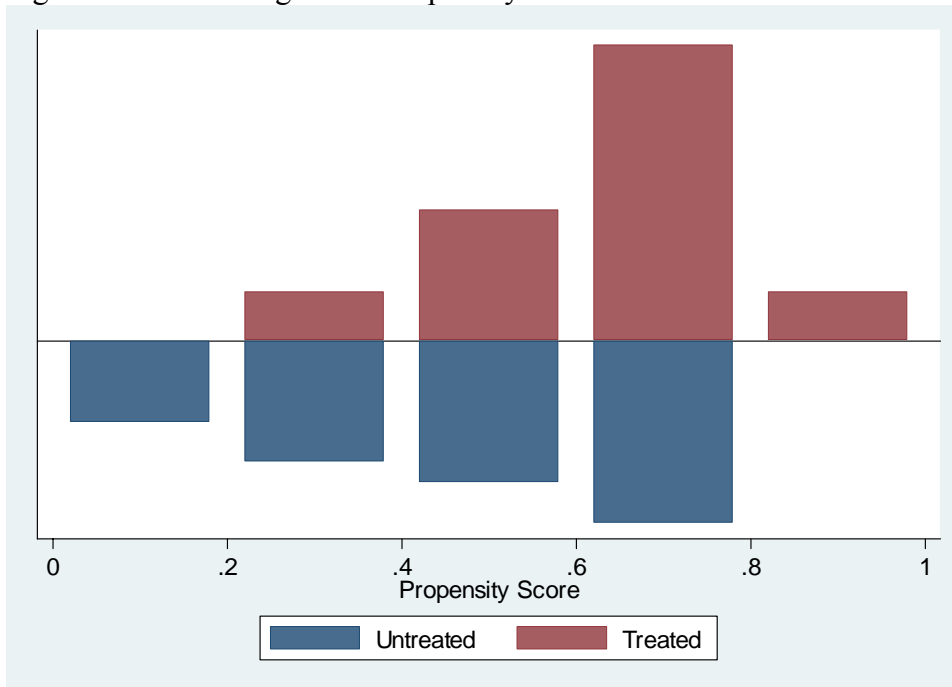
Table 5 lists the logit model results. Figure 3 is a histogram of propensity scores and illustrates the intervals of common support, which was selected as

[.28674648, .91886112]. Four non-participant observations fall below the lower bound of common support and are omitted from the calculation of the average treatment effect on treated (ATET). Table 6 lists the distribution of propensity scores.

Table 5. Logit Estimates of the Coefficients of Participation

Independent Variable	Coefficient	SE Coefficient	P-value
Constant	-1.00486	1.12749	0.373
Farm500-999	0.0095844	0.0197394	0.6270
NumFirms	-0.0001782	0.0001129	0.114
PerAgStream	0.106273	0.116379	0.361
EQIPfy02-03	0.145102	0.0853441	0.089

Figure 3. Histogram of Propensity Scores



Frequency of participants (treated) is top segment of bar graph

Frequency of non-participants (untreated) is bottom segment of bar graph

Table 6. Estimated Distributions of Propensity Score

Propensity Score	Non-participant	Participant	Total	Common Support Total
0.0 – 0.2	4	0	4	0
0.2 – 0.4	6	3	9	9
0.4 – 0.6	7	8	15	15
0.6 – 0.8	9	18	27	27
0.8 – 1.0	0	3	3	3
Total	26	32	58	54

The region of common support is [.28674648, .91886112]

Balancing property for all covariates for each block has been satisfied.

Assessing the Matching Quality

Table 7 lists the results from balancing the propensity score and covariates within blocks. For each of the 3 blocks that contain propensity scores and covariates for both participant and non-participants the standard t-test for difference in means results in p-values in which the null hypothesis of no difference in means cannot be rejected at a level of significance 0.10. It is this balancing condition that results in the distributions of the likelihood of participation (i.e. propensity score) conditioned on a set of county attributes being similar for participants and non-participants.

Caliendo (2005) identifies several methods to assess the matching quality of selected covariates to check if the matching procedure is able to balance the distribution of the relevant variables in both the participant and non-participant groups. The basic idea is to compare the situation before and after matching and check if there remain differences after conditioning on the propensity score. Inspection of the results listed in Table 7 reveals results that are consistent with the balancing requirement that after matching the difference in propensity score means and the covariates for the participants and non-participants are not statistically significant (Dehejia and Wahba 1998).

Sianesi (2004) suggests re-estimating the propensity score on the matched sample and comparing the pseudo- R^2 's before and after matching. The pseudo- R^2 indicates how well the regression covariates explain the participation probability. After matching there should be no systematic differences in the distribution of covariates between participants and non-participants. Therefore, the pseudo- R^2 should be fairly low. The pseudo- R^2

Table 7 Balancing on Propensity Scores

Covariate	Block	Mean for Non-participant	Mean for Participant	P-value for two-sided t-test of difference in means $\Pr(T > t) =$
Propensity score	1	n=0	n=0	
Farm500-999	1	n=0	n=0	
NumFirms	1	n=0	n=0	
PerAgStream	1	n=0	n=0	
EQIPfy02-03	1	n=0	n=0	
Propensity Score	2	.3278005 (.0137141) n=6	.350545 (.055284) n=3	0.3446
Farm500-999	2	21.16667 (14.5522) n= 6	27.66667 (34.77547) n=3	0.6924
NumFirms	2	4928.5 (2569.635) n=6	5401.333 (2806.503) n=3	0.8073
PerAgStream	2	5.634667 (1.511095) n=6	6.512333 (.682916) n=3	0.3812
EQIPfy02-03	2	2.5 (3.016621) n=6	2.666667 (2.081666) n=3	0.9348
Propensity Score	3	.4660982 (.0267882) n=7	.491824 (.0462998) n=8	0.2196
Farm500-999	3	23.14286 (5.984106) n=7	20.125 (5.984106) n=8	0.4497
NumFirms	3	2902.571 (2760.091) n=7	2321.25 (2359.044) n=8	0.6671
PerAgStream	3	6.663286 (1.634976) n=7	6.9555 (2.357865) n=8	0.7879
EQIPfy02-03	3	3.142857 (1.9518) n=7	3.125 (3.226564) n=8	0.9900
Propensity Score	4	.703255 (.0807809) n=9	.700214 (.05493) n=18	0.9088
Farm500-999	4	30.55556 (18.6421) n=9	32.55556 (16.40022) n=18	0.7775
NumFirms	4	1898.778 (1417.052) n=9	2297.389 (1417.052) n=18	0.7024
PerAgStream	4	9.927667 (2.760862) n=9	10.28933 (2.760862) n=18	0.7468
EQIPfy02-03	4	6.111111 (2.934469) n=9	6 (4.537426) n=18	0.9475

Covariate	Block	Mean for Non-participant	Mean for Participant	P-value for two-sided t-test of difference in means $\Pr(T > t) =$
Propensity Score	5	n=0	n=3	
Farm500-999	5	n=0	n=3	
NumFirms	5	n=0	n=3	
PerAgStream	5	n=0	n=3	
EQIPfy02-03	5	n=0	n=3	

associated with the logit regression using the full data set is 0.15, and after matching, the logit regression using the matched observations is 0.02.

An F-test for the joint significance of the covariates prior to matching has a p-value of 0.017, and after matching the F-test for joint significance has a p-value of 0.84. One wants the F-test to be significant when the initial propensity scores are estimated using the logit regression because participants and non-participants differ in their attributes. The coefficients reflect these differences and for a model constructed to explain the probability of participation one wants to reject the hypothesis that all coefficients are zero. After selecting those participants and non-participants who are similar in terms of the selected covariates, differences should no longer be present. If the logit model is re-estimated using the reduced sample of matched observations, there are no differences in the two groups, and the regression coefficients should not be significant corresponding to a higher p-value.

The results from the t-tests for differences in propensity score means and the covariates, the comparison of pseudo- R^2 , and the comparison of F-tests are consistent with the model being estimated with a balanced set of covariates.

Table 8 lists the counties by propensity score within blocks. A small data set allows for direct comparison of matched participant and non-participant counties.

Randomization of participation and non-participation to a program results in independent

and identical distributions of observable and non-observables for participants and non-participants. It is this outcome that allows for the direct estimation of program impact by calculating the difference in mean outcome for participants and non-participants to be an unbiased estimator of the program impact.

Estimation by matching on propensity scores attempts to emulate this outcome by construction of similarity of distributions for the observable attributes for participants and non-participants. It is the similarity of these distributions that allows for the substitution of non-participants outcomes for the expected outcome of participants as if they did not participate in the programs, which is the missing counter-factual. This is premised on the assumption that the decision to participate is not influenced by unobservable county attributes.

Table 8. Propensity Scores within Common Support by Block by County

	code	county	treatment	Rate04	PS1	match	block	comsup	weight
1	58	SUSQUEHANNA	1	3	0.918861	1	5	1	
2	49	NORTHUMBERLAND	1	4.2	0.898891	1	5	1	
3	56	SOMERSET	1	2.1	0.873308	1	5	1	
4	20	CRAWFORD	0	2.5	0.792762	1	4	1	3
5	29	FULTON	1	4.5	0.789106	1	4	1	
6	59	TIOGA	0	2.7	0.787744	1	4	1	1
7	63	WASHINGTON	0	1.1	0.787231	1	4	1	1
8	55	SNYDER	1	1.8	0.783845	1	4	1	
9	53	POTTER	1	4.1	0.779303	1	4	1	
10	30	GREENE	0	1.4	0.772073	1	4	1	3
11	1	ADAMS	1	1.3	0.753913	1	4	1	
12	7	BLAIR	1	4	0.72902	1	4	1	
13	5	BEDFORD	1	0.7	0.719946	1	4	1	
14	28	FRANKLIN	1	2.5	0.711235	1	4	1	
15	31	HUNTINGDON	1	0.6	0.710117	1	4	1	
16	18	CLINTON	1	2.6	0.709527	1	4	1	
17	50	PERRY	1	0.9	0.705211	1	4	1	
18	15	CHESTER	1	2.3	0.694436	1	4	1	
19	32	INDIANA	1	1.3	0.682954	1	4	1	
20	64	WAYNE	0	1.8	0.67347	1	4	1	8
21	47	MONTOUR	1	1.3	0.67337	1	4	1	
22	21	CUMBERLAND	1	1.6	0.657171	1	4	1	
23	62	WARREN	0	0.2	0.653515	1	4	1	1
24	42	MCKEAN	0	1.5	0.652683	1	4	1	2
25	11	CAMBRIA	1	1.3	0.640881	1	4	1	
26	14	CENTRE	1	1.2	0.6387	1	4	1	
27	34	JUNIATA	1	1.4	0.620738	1	4	1	
28	3	ARMSTRONG	0	3.8	0.606295	1	4	1	1
29	44	MIFFLIN	1	0.7	0.604382	1	4	1	
30	4	BEAVER	0	0.3	0.603522	1	4	1	1
31	57	SULLIVAN	1	2.9	0.546776	1	3	1	
32	66	WYOMING	1	1.4	0.541326	1	3	1	
33	41	LYCOMING	1	0.3	0.533112	1	3	1	
34	43	MERCER	0	1.8	0.510245	1	3	1	4
35	60	UNION	1	0.2	0.497592	1	3	1	
36	19	COLUMBIA	1	2	0.488517	1	3	1	
37	33	JEFFERSON	0	2	0.478397	1	3	1	1
38	61	VENANGO	0	1.3	0.476548	0	3	1	0
39	26	FAYETTE	0	1.4	0.469124	0	3	1	0
40	16	CLARION	0	0.7	0.45881	1	3	1	1
41	17	CLEARFIELD	1	1.7	0.457955	1	3	1	
42	40	LUZERNE	1	1.1	0.441843	1	3	1	
43	37	LAWRENCE	0	1.4	0.440807	1	3	1	1
44	65	WESTMORELAND	0	1.5	0.428757	1	3	1	1
45	54	SCHUYLKILL	1	1.2	0.42747	1	3	1	
46	38	LEBANON	1	1.4	0.384352	1	2	1	
47	6	BERKS	1	2	0.380536	1	2	1	
48	48	NORTHAMPTON	0	4.1	0.348769	1	2	1	2
49	39	LEHIGH	0	0.8	0.333262	0	2	1	0
50	25	ERIE	0	0.6	0.33303	0	2	1	0
51	13	CARBON	0	1.9	0.324649	0	2	1	0
52	10	BUTLER	0	0.9	0.317238	0	2	1	0
53	45	MONROE	0	1.2	0.309856	1	2	1	1
54	35	LACKAWANNA	1	- 4.2 -	0.286747	1	2	1	

In the matching literature using propensity scores there are several algorithms for selecting pairs of participant and non-participant propensity scores for purposes of matching the outcome variable. The method used for this paper consists of nearest neighbor matching with replacement and radius matching. Nearest neighbor matching sets

$$C(i) = \min_j \| p_i - p_j \|$$

Where:

$C(i)$ = the set of control units matched to the treated unit i with an estimated propensity score of p_i .

$C(i)$ is a singleton, unless there are multiple nearest neighbors.

Radius matching is defined as:

$$C(i) = \{ p_j \mid \| p_i - p_j \| < r \}$$

All the control units with estimated propensity scores falling within a radius r from p_i are matched to the treated unit i . Depending on the specification of r , radius matching can be used to increase the number of control units used, especially when the data set is small.

The formula for both types of matching estimators can be written as:

$$ATET = \frac{1}{N} \sum_{i \in T} Y_i - \frac{1}{N} \sum_{j \in C} w_j Y_j$$

Where the weights w_j are defined by $w_j = \sum_i w_{ij}$. The weight assigned to a unit is the frequency the control unit was used as a match. This value for nearest neighbor matching was calculated by inspection and is listed in Table 8.

Table 9 contains the descriptive statistics for the absolute value propensity-score difference between participants and non-participants are:

Table 9. Average Absolute Propensity Score Difference Between Participant and Non-participant

Variable	Observations	Mean	Std Deviations	Min	Max
Propensity Score	32	0.0267	0.0296	0.00009	0.12

Estimates of ATET are listed in Table 10 for both nearest neighbor and radius matching.

Table 10. Estimates of ATET

Nearest Neighbor							
	Observations	Weight	Mean	Std. Deviations	Min	Max	t
Participant Rate	32		1.809	1.16	0.2	4.4	
Non-participant Rate	16	32	1.85	0.90	0.2	4.1	
ATET			-0.047	0.422			-0.111
Radius Matching with $r = 0.01$							
	Observations	Weight	Mean	Std. Deviations	Min	Max	t
Participant Rate	10		1.93	1.291898	0.7	4.5	
Non-participant Rate	12	10	1.711111	0.96162	0.2	3.8	
ATET			0.219	0.528			0.415
Radius Matching with $r = 0.05$							
	Observations	Weight	Mean	Std. Deviations	Min	Max	t
Participant Rate	29		1.675862	1.103778	0.2	4.5	
Non-participant Rate	22	29	1.532979	0.904747	0.2	4.1	
ATET			0.143	0.317			0.451
Radius Matching with $r = 0.10$							
	Observations	Weight	Mean	Std. Deviations	Min	Max	t
Participant Rate	30		1.69	1.087341	0.2	4.5	
Non-participant Rate	22	30	1.609453	0.980282	0.2	4.1	
ATET			0.081	0.303			0.265

Concluding Remarks

The average treatment effect on the treated (ATET) is listed in Table 10. The range of the ATET is from -0.047 to 0.219. The ATET is interpreted as the difference in participation rate for participants with and without the Chesapeake Bay Program. The null hypothesis that the difference in means is different from zero cannot be rejected for any of the four ATET estimates. Given the common support criteria for selecting observations for matching, the estimate of ATET is limited to those participant counties with propensity scores with the interval [.28674648, .91886112].

The formulas to analytically calculate the standard errors of the mean participant and non-participant EQIP rate are contained in Becker and Ichino 2002. The Stata software program for average treatment effect on the treated (Stata command: `attnd`) includes options for estimating standard errors using boot-strapping. The estimate of ATET standard error using boot-strapping with nearest neighbor matching and 100 replications is 0.448. This compares closely to the calculated standard error of 0.422.

The selected set of covariates for estimating the propensity score using a logit model resulted in estimated coefficients with signs that are consistent with expected direction of correlation based upon prior studies. The number of farms with 500 to 999 acres and the percentage of county agricultural land within 150 feet of a waterway were associated with a positive effect on the likelihood of a county choosing to participate in the Chesapeake Bay Program. The number of non-farm establishments with paid employees and the number of housing units are negatively associated with likelihood of participation. The total number of funded EQIP applications in a county for the years prior to choosing to participate displays a positive effect, indicating that prior year performance of the program influences the likelihood of a county to re-apply for participation in the CBP.

This study did not identify a statistically significant impact of the Chesapeake Bay Program in Pennsylvania on county application rates for the Environmental Quality Incentive Program during FY2004. Estimation of the impact of the CBP on EQIP participation rates can be enhanced by investigating its potential impact using a data set that includes observation of EQIP rates over time, such as a period FY2003 – 2005. Further work needs to be conducted to increase the sample size either by increasing the period of participation or extending the study area to encompass the entire Chesapeake Basin. Extending to the entire basin will also significantly increase the occurrence of confounding factors because each state participates in the CBP uniquely with its own set of state regulations and programs. Limiting the study area to Pennsylvania for this initial analysis is consistent with Smith's (2006) recommendation that when using matching to evaluate program effects one should compare participants and non-participants who are affected by similar economic market conditions.

Tests are proposed to evaluate the sensitivity of ATET to unobserved differences between participants and non-participants (Caliendo 2006). In light of the results for this study not being significant such evaluation is not conducted.

Although this paper does not identify a statistically significant program impact on farmers' willingness to enroll in EQIP, further areas for investigation could include the impact of the CBP on other conservation programs such as Conservation Reserve Program, Wetland Reserve Program, and the Conservation Reserve Enhancement Program.

The estimation of EQIP participation rates may be improved by use of the Farm Service Agency (FSA) county counts of farm operators who participate in USDA farm conservation programs. The 2002 Agricultural Census count of farms by county includes

multiple farms owned by a single operator. Furthermore, stratification of farm operators, such as farm operators belong to the Amish and Mennonite communities, commonly choose not to participate in any USDA funded programs. Similarly for operators of very small farms or retirees who do not participate in USDA farm conservation programs. Narrowing the set of farmers who are potential participants in EQIP may improve the estimation of program participation rate.

Additional challenges confronting estimating the CBP impact was cited earlier when discussing that occurrence that signatory state enact laws and regulations in response to CBP goals, and as such the state regulations are imposed state-wide. Thus, state-sponsored CBP initiatives likely have spill-over effects that extend outside of the Chesapeake Bay basin. Thus while matching is conducted using participant and non-participant CBP counties, the response variable EQIP applications rates may serve as a good indicator of an outcome uniquely impacted by the CBP. Further research on the identification and selection of an outcome variable could be achieved by closer inspection of what the expected goals of the Pennsylvania Department of Environmental Protection (DEP) CBP are. Such information may possibly be obtained by reviewing the contracts county participants complete for the purpose of identifying expected outcomes.

Personal conversations with EQIP program specialists revealed their expectation that EQIP program benefits from the Chesapeake Bay program. This is the first attempt to try and estimate that impact. Although no statistically significant impact was identified, the application of matching on propensity scores revealed additional areas for research that warrant further consideration.

APPENDIX A

List of Variables Considered as County Covariates for Matching

Variable	Treatment Correlation	Rate Correlation
1 Conservation Reserve Payments (dollars)	0.631	0.074
2 Net Farm Income (dollars)	0.538	0.112
3 Phosphorus source transport index	0.534	0.077
4 Percent Dairy Farms	0.493	0.149
5 Acres covered by nutrient management plans	0.482	0.154
6 Animal Equivalent Units (AEU) per acre	0.474	-0.043
7 Percent Republican Presidential Vote 2004	0.441	0.303
8 Mean soil phosphorus level (ppm)	0.439	-0.154
9 Percent county land used for crop production	0.433	0.102
10 Acres treated with manure	0.419	0.065
11 Percent county land used for corn production	0.418	0.076
12 Farm Operating loans (dollars)	0.415	0.09
13 Number of nutrient management plans	0.405	0.047
14 Percent agricultural land	0.382	0.011
15 Percent of soil samples exceeding 50ppm phosphorus	0.369	-0.158
16 Number of farms applying manure	0.358	0.026
17 Number of farms 500 to 999 acres	0.355	0.286
18 Number of EQIP contracts FY2002 and FY2003	0.349	0.179
19 Percent of Farms with farming primary occupation	0.341	-0.013
20 Number of cattle	0.34	0.075
21 Farms with sales exceeding 1000 (thousands dollars)	0.332	-0.001
22 Number of poultry	0.33	-0.045
23 Number of acres irrigated	0.313	-0.113
24 Number of hogs	0.307	-0.016
25 Number of dairy farms	0.301	0.026
26 Farm acreage	0.291	0.079
27 EQIP Obligations FY2002 and FY2003	0.29	0.18
28 Average soil phosphorus levels	0.282	-0.188
29 Number of farms 180 to 499 acres	0.281	0.177
30 Number of acres covered by farm conservation easement	0.281	-0.086
31 Number of farms with farming primary occupation	0.275	-0.034
32 Number of farms with 1000 acres or more	0.27	0.108
33 Percent of agricultural land within 150 feet of stream	0.264	0.323
34 Number of acres covered by EQIP as of FY2003	0.263	0.243
35 Mean value of equipment per farm (dollars)	0.26	0.137
36 Number of farms	0.254	-0.047
37 Farms with sales 500 to 999 (thousands dollars)	0.253	-0.018
38 Farms with sales 250 to 499 (thousands dollars)	0.248	-0.049
39 Percent change in housing stock	0.236	-0.069
40 Farms with 1 to 9 acres	0.235	-0.069
41 Farms with sales 100 to 249 (thousands dollars)	0.234	-0.067
42 Number of poultry farms	0.234	-0.054
43 Number of farm conservation easements	0.23	-0.089
44 Number of cattle farms	0.222	0.001

	Variable	Treatment Correlation	Rate Correlation
45	Farms with 10 to 49 acres	0.217	-0.124
46	Farms with 50 to 179 acres	0.21	-0.058
47	Number of hog farms	0.196	-0.041
48	Percent of cattle farms	0.162	0.147
49	Percent soil samples exceeding 300ppm phosphorus	0.157	-0.163
50	Percent soil samples exceeding 200ppm phosphorus	0.149	-0.192
51	Farms with less than 10,000 sales revenue	0.143	-0.065
52	Farm Operating loans (dollars)	0.134	0.077
53	Farms with sales 50 to 99 (thousand dollars)	0.129	-0.094
54	Farms with sales 25 to 49 (thousands dollars)	0.103	-0.058
55	Percent of population with only high school degree	0.1	0.23
56	Federal highway grants (dollars)	0.065	-0.151
57	Percent change in population 2000 - 2004	0.04	-0.172
58	Median income as a percent of state median	0.027	-0.122
59	Median income	0.024	-0.12
60	Number of dairy farms	-0.004	0.032
61	Number of beef cows	-0.006	0.033
62	Number of hunting licenses	-0.018	-0.196
63	Housing construction permits	-0.032	-0.143
64	Number of beef farms	-0.043	-0.004
65	Percent of hog farms	-0.052	0.092
66	Percent of poultry farms	-0.055	-0.086
67	Percent of population with college degrees	-0.062	-0.171
68	Percent of livestock farms	-0.064	0.139
69	Industrial groundwater withdrawal	-0.108	0.014
70	Percent of forest cover	-0.137	0.129
71	Water land ratio	-0.142	-0.111
72	Total direct federal expenditure	-0.177	-0.222
73	Density	-0.186	-0.178
74	Population 2004	-0.192	-0.226
75	Population 2000	-0.194	-0.227
76	Unemployment rate	-0.197	0.067
77	Number of firms	-0.203	-0.21
78	Number of housing units	-0.233	-0.228
79	Percent of beef farms	-0.32	0.101

Bold print indicates the variable's correlation coefficient is high relative to other variables for both the Treatment variable and the Rate04 variable.

References

- Becker, S. O., and Andrea Ichino 2002. "Estimation of Average Treatment Effects Based on Propensity Scores." The Stata Journal 2(4): 358-377.
- Borland, J., Yi-Ping Tseng, and Roger Wilkins 2005. Experimental and quasi-experimental methods of microeconomic program and policy evaluation. Melbourne, Melbourne Institute of Applied Economics and Social Research: 43.
- Blundell, R., and Monica Costa Dias 2002. Alternative Approaches to Evaluation in Empirical Microeconomics. London. The Institute for Fiscal Studies Department of Economics University College London: 38.
- Boesch, D., R. B. Brinsfield, et al. 2001. "Chesapeake Bay Eutrophication: Scientific Understanding, Ecosystem Restoration, and Challenges for Agriculture." *Journal of Environmental Quality* 30: 303-320.
- Caliendo, M., and Sabine Kopeinig 2005. Some Practical Guidance for the Implementation of Propensity Score Matching. Bonn, Institute for the Study of Labor: 29.
- Chen, Wen-Hao 2004. Essays on Employment Insurance, Income Mobility, and Family Income Distribution. Dissertation Michigan State University.
- Cronin, E. 1967. The Condition of the Chesapeake. 32 North American Wildlife and Natural Resources Conference, Washington, D.C.
- Dehejia, R., H. and Sadek Wahba 1998. Propensity Score Matching Methods for Non-Experimental Causal Studies, National Bureau of Economic Research: 32.
- Ernst, H. R. 2003. Chesapeake Bay Blues Science, Politics, and the Struggle to Save the Bay, Rowman and Littlefield.
- Fisher, R. 1935. Design of Experiments. Hafner, New York.
- Frondel, M., and Christoph M. Schmidt 2001. Evaluating Environmental Programs: The Perspective of Modern Evaluation Research, Institute for the Study of Labor: 24.
- Government Accounting Office 2005. Chesapeake Bay Program Improved Strategies Are Needed to Better Assess, Report, and Manage Restoration Progress. Washington D.C., United States Government Accountability Office: 87.
- Greenstone, M. 2004. "Did the Clean Air Act cause the remarkable decline in sulfur dioxide concentrations?" *Journal of Environmental Economics and Management* 47: 585-611.

Heckman, J. J., Hidehiko Ichimura, and Petra Todd 1997. "Matching As an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Program." *Review of Economic Studies* 64: 605-654.

Hill, J. L., J.P. Reiter, and E.L. Zanutto 2004. A Comparison of experimental and observational data analyses. Applied Bayesian Modeling and Casual Inference from Incomplete Data Perspective. New York, Wiley.

Horton, T. and W. M. Eichbaum 1991. Turning the Tide Saving the Chesapeake Bay. Washington, D.C., Island Press.

Imbens, G. W. 2004. "Nonparametric Estimation of Average Treatment Effects under Exogeneity: A Review." *Review of Economics and Statistics* 86(1): 4-29.

Knapp, G. 1998. Environmental Program Evaluation A Primer. Urbana, University of Illinois Press.

List, J. A., Daniel L. Millimet, Per G. Fredriksson, and Warren McHone 2003. "Effects of Environmental Regulations on Manufacturing Plant Births: Evidence from a Propensity Score Matching Estimator." *The Review of Economics and Statistics* 85(4): 944-952.

List, J. A., Daniel L. Millimet, and Warren McHone 2004. "The Unintended Disincentive in the Clean Air Act." *Advances in Economic Analysis and Policy* 4(2): 26.

Neyman, J. 1935. "Statistical Problems in Agricultural Experiments" *The Journal of the Royal Statistical Society* 2(2), 107-180.

Norris, P., Sandra Batie 1987. "Virginia Farmers' Soil Conservation Decisions: An Application of Tobit Analysis." *Southern Journal of Agricultural Economics*.

Pennsylvania Department of Environmental Protection. 2002. Pennsylvania's Chesapeake Bay Nutrient Reduction Strategy. Harrisburg, Pennsylvania Department of Environmental Protection: 46.

Pierno, T. 2004. Statement of Theresa Pierno, Vice President for Environmental Protection and Restoration, Chesapeake Bay Foundation before Committee on Government Reform Hearings on Safeguarding the Chesapeake Bay. August. Washington D.C.

Portney, P. R., Robert N. Stavins 2000. Public Policies for Environmental Protection. Washington D.C., Resources for the Future.

Ribaudo, M., and Richard Horan, and Mark Smith 1999. Economics of Water Quality Protection from Nonpoint Sources. Washington, D.C., Economic Research Service: 105.

Rosenbaum, P. R. 1995. Observational Studies. New York, Springer-Verlag.

Rosenbaum, P. R., and Donald B. Rubin 1983. "The Central Role of the Propensity Score in Observational Studies for Casual Effects." *Biometrika* 70(1): 41-55.

Rosenbaum, P. R., and Donald B. Rubin 1985. "Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score." *The American Statistician* 39(1): 33-38.

Rubin, D. B. 1974. "Estimating Casual Effects of Treatments in Randomized and Nonrandomized Studies." *Journal of Educational Psychology* 66(5): 688-701.

Rubin, D. B. 1976. "Inference and Missing Data." *Biometrika* 63(3): 581-92.

Rubin, D. B. 1977. "Assignment to Treatment Group on the Basis of Covariate." *Journal of Educational Statistics* 2(1): 1-26.

Russell, C. S., and Jason F. Shogren 1993. Theory, Modeling and Experience in the Management of Nonpoint Source Pollution. London, Kluwer Academic Publishers.

Smith, H. L. 1997. "Matching with Multiple Controls to Estimate Effects in Observation Studies." *Sociological Methodology* 27: 325-353.

Smith, J. 2006. Lecture notes for Economics 675 Empirical Microeconometrics, University of Michigan: 16.

Staver, K., Russell B. Binsfeld 2001. "Agriculture and Water Quality on the Maryland Eastern Shore: Where Do We Go from Here?" *BioScience* 51(10): 859-868.

Susskind, L. E., Ravi K. Jain, and Andrew O. Martyniuk 2001. Better Environmental Policy Studies. Washington, Island Press.

United States Department of Agriculture 2003. Environmental Quality Incentives Program Benefit Cost Analysis. Washington D.C., United States Department of Agriculture: 50.

Wennersten, J. R. 2001. The Chesapeake an Environmental Biography. Baltimore, Maryland Historical Society.

Winship, C., and Michael Sobel 2004. Casual Inference in Sociological Studies in Handbook of Data Analysis. London, Sage Publications.

Wooldridge, J. 2002. Econometric Analysis of Cross Section and Panel Data. Cambridge, MIT Press.

Zinn, J., and Carol Canada 2005. Environmental Quality Incentives Program (EQIP): Status and Issues. Washington D.C., Congressional Research Service: 6.

Zinn, J., and Tadlock Cowan 2005. Agriculture Conservation Programs: A Scorecard. Washington D.C., Congressional Research Service: 17.